Studying Bitcoin Miners' Strategies Under Uncertainty

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Abstract

We introduce a Bayesian game-theoretic and simulation-based framework to study Bitcoin miner behavior under uncertainty. Each miner draws a private type that includes exogenous and endogenous variables such as electricity costs, hardware efficiency, and risk aversion. Strategies involve hash rate commitment and pool participation. By sampling these types and simulating strategic responses across market scenarios, we approximate Bayesian Nash Equilibria through Monte Carlo simulations, showing how type distributions and market volatility affect equilibrium outcomes. We define discrete mining pool categories with different fee structures and classify external environments into high, medium, and low profiatbility contexts. This structured model enables equilibrium benchmarking, risk analysis, and policy testing in decentralized mining networks.

1 Introduction

Bitcoin's Proof-of-Work (PoW) consensus relies on decentralized mining, where each participant invests computing resources to earn block rewards and transaction fees. Due to volatile market prices, fluctuating network hash rate, and spatially heterogeneous electricity costs, mining profitability is highly uncertain. Moreover, miners differ significantly in hardware performance and risk tolerance. These heterogeneities and information asymmetries motivate a Bayesian game-theoretic modeling approach [2, 3].

In this paper, we define miners as players in a one-shot[1] Bayesian game with private types and incomplete information. Each miner selects a strategy (how much to mine and whether to join a pool) to maximize expected utility based on beliefs about others. To approximate equilibrium outcomes in realistic settings, we implement a Monte Carlo simulation engine informed by real-world mining hardware, cost distributions, and network parameters.

[1] each player makes one decision, all decisions are made simultaneously, and there are no future rounds.

2 Bayesian Game Formulation

We model the Bitcoin mining competition as a one-shot Bayesian game with incomplete information. Let there be N miners. Each miner i has a private type vector:

$$\theta_i(c_i, \eta_i, \kappa_i, \rho_i, \phi_i) \tag{1}$$

where: c_i is the electricity price (\$/kWh), η_i represents the energy efficiency (J/TH), κ_i is the capacity (TH/s), ρ_i is the risk tolerance (0-1), and ϕ_i is the strategic preference (e.g., solo vs pool mining). Each miner choses an action, or strategy $s_i \in S$:

- individual hash rate $h_i \in \big[0, \kappa_i\big]$,
- strategy or mode of operation $m_i \in \big\{\texttt{s}, \texttt{p}_{\{\texttt{b},\texttt{m},\texttt{s}\}}, \texttt{o}\big\}$, where they stand for:solo and pool mining, or offline. Pool is divided in big, medium, or small mining pools.

Formally, a Bayesian Nash equilibrium (BNE) is a profile of strategy functions $\big\{s_i^*(\theta_i)\big\}_{i=1}^N$, such that for each miner i, their equilibrium strategy maximizes expected utility, given their beliefs over others' types and assuming others follow their equilibrium strategies:

$$s_i^*(\theta_i) \in \arg\max_{s_i} \mathbb{E}_{\theta_{-i}}\big[u_i(s_i(\theta_i), s_{-i}^*(\theta_{-i}); \theta_i)\big] \tag{2}$$

where θ_{-i} denotes the types of all miners except i, $s_{-i}^*(\theta_{-i})$ are the equilibrium strategies of other miners, and $u_i(\cdot)$ is miner i's utility function, which depends on their action, others' actions, and their private type. The expected utility is taken over miner i's beliefs about the types of other miners, typically assumed to be independently drawn from a known distribution. Since miners do not observe each other's electricity cost or risk profile, they must reason strategically under uncertainty, using probabilistic beliefs about the rest of the network. The expected utility is :

$$u_i = \mathbb{E}\left[\frac{h_i}{H}(R + M)P(1 - f_s) - k_i h_i\right] \tag{3}$$

where H is the total network hash rate, R is the block reward, M is the sum of transaction fees, P is the Bitcoin price, $k_i = \frac{\eta_i}{10^6}$ is the cost per hash, f_s is the pool fee based on selected strategy s_i. Table 1 shows our values for different pool categories with a relative fee overcharge for earnings.

Pool Type	**Hash Share (%)**	**Fee (%)**
Small Pool (s)	$< 1\%$	0.0%
Medium Pool (m)	1–5%	1.0%
Large Pool (b)	$> 5\%$	2.5%

Table 1: Classification of mining pool types by size and fee

3 Market Scenarios and Monte Carlo Simulation Setup

We define three mining environments to capture macroeconomic variation. We define them as *good*, *average*, and *bad* environment to mine, and they are defined in Table 2. Miners draw types from empirical or synthetic distributions. The electricity price c_i is drawn from a multi-modal distribution (e.g., India, US, UK); η_i and κ_i are drawn from a dataframe of Application Specific Integrated Circuits (ASIC) models (e.g., Antminer S19 series); ρ_i is drawn from a uniform distribution over the interval $[0, 1)$, equivalent to a Beta(1,1) distribution; and ϕ_i is sampled via uniform assignment. Such scenarios reflect historically grounded boundary conditions of Bitcoin profitability cycles (e.g., bull runs, corrections, and downturns), and they allow factorial analysis of how equilibrium behavior shifts as a function of external contraints, holding miner type fixed.

Scenario	**BTC Price [$]**	**Hashrate [EH/s]**	**Fee $\times$ Block [BTC]**
Good	100,000	400	0.8
Average	60,000	600	0.4
Bad	25,000	1000[2]	0.1

Table 2: Definition of mining environments used in simulations

For each scenario, we repeat the simulation for 10^8 draws to approximate miner behavior in expectation. In each run:

1. All miner types $\theta_1, \cdots, \theta_N$ are sampled independently.
2. An initial strategy profile is assigned (e.g., hash rate set to capacity or zero).
3. Each miner iteratively updates their action to maximize expected payoff given others' current strategies.
4. The system converges to a stable proofile (or ϵ-equiibrium), which is logged for statistical aggregation.

By comparing equilibrium outcomes across scenarios, we can identify *regime-dependent thresholds* (e.g., the cost level above which miners go offline) and shifts in pool participation (e.g., small pools vanish in bad markets). The scenario-based structure also enables policy simulations, such as testing whether modifying fee dynamics or imposing carbon taxes would alter the strategic landscape for miners.

4 Results and Discussion

Figure 1 shows simulation results (10M draws per scenario) acroos three market conditions (good, average, bad) and electricity regimes (India, US, UK). Each panel displays normalized hash rate (left axis) and mean risk aversion (right axis) by strategy: solo, pool, or offline.

[2] current total Bitcoin hash rate $H \simeq 990$ EH/s.

In good markets, almost all miner participate; low-cost regions like India support both solo and pooled mining, while higher-cost regions rely almost exclusively on pooling. Risk-averse miners cluster in pools, while risk-prone ones prefer solo mining. In average markets, high-cost miners begin exiting. The US shows a shift toward offline status, while India remains stable. Pooling dominates across all active miners. In bad markets, nearly all high-cost miners go offline. Only low-cost miners in India remain acrive, splitting between pooling and shutdown . Solo mining vanishes across all regions.

Across scenarios, risk aversion increases pooling, and cost determines survival. Pooling functions as a risk mitication tool until profitability thresholds are breached.

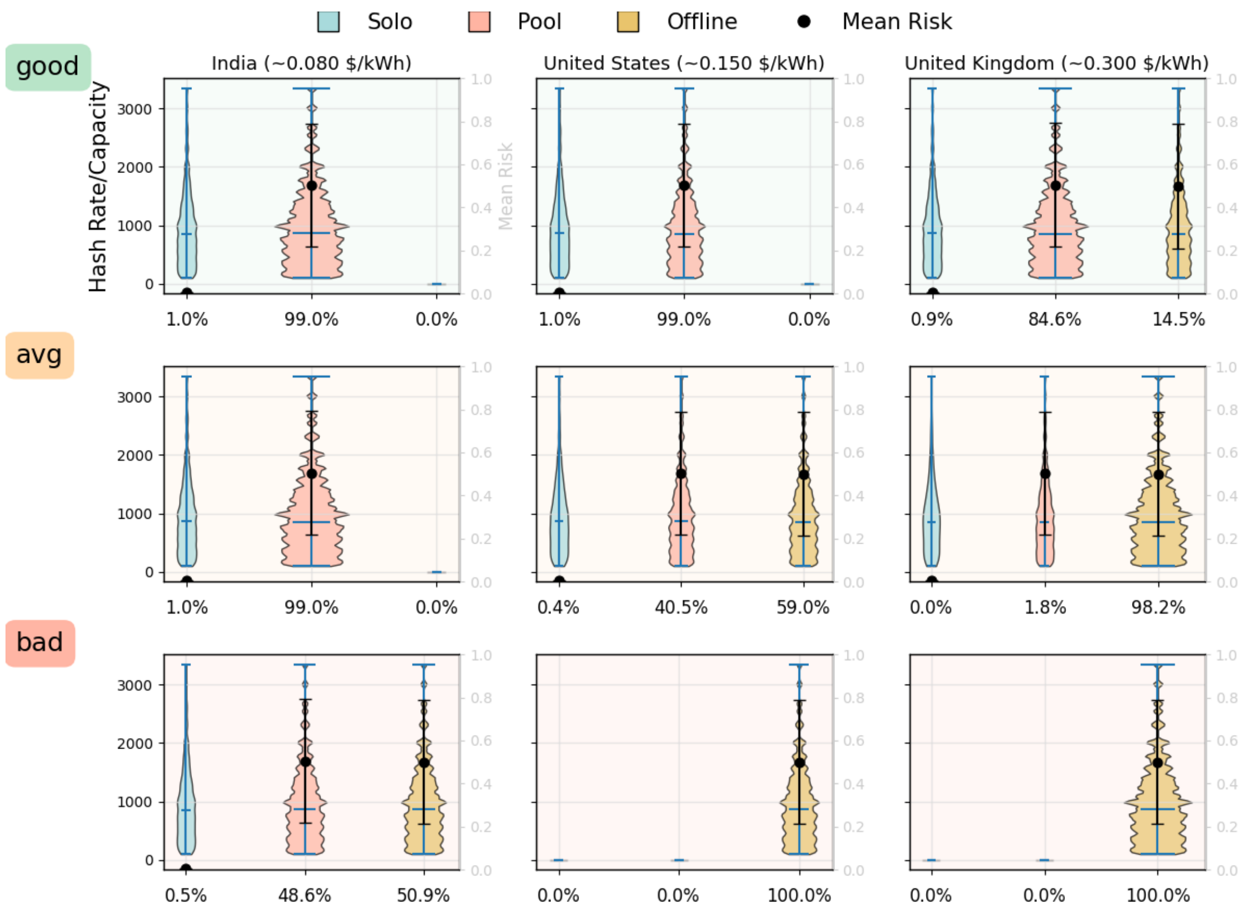

Figure 1: Monte Carlo simulation results (10M samples per scenario). Each row corresponds to a market condition (good, average, bad), and each column to an electricity price regime (India, US, UK). Violin plots show normalized hash rate (left axis) and mean risk aversion (right axis) by miner strategy.

5 Conclusion

Our simulations show how miner strategies respond to market and cost heterogneity. Key outcomes are: (i) low-cost miners persist and pool, while high-cost miners strategy is to go offline under pressure; (ii) risk aversion drives pooling, but cannot sustain mining in low-profit regimes; (iii) solo mining is rare, surviving only in optimal conditions with low cost and low risk aversion.

This framework enables analysis of equilibrium miner behavior under uncertainty and can support future policy simulations and real-world calibration.

References

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